MULTI-AGENT CLASSIFIER SYSTEM BASED ON HETEROGENEOUS CLASSIFIER

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Bachelor of Computer Science (Software Engineering).

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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Thesis submitted in fulfillment of the requirements
for the award of the degree of
Bachelor of Computer Science (Software Engineering)

Faculty of Computer System & Software Engineering
UNIVERSITI MALAYSIA PAHANG

DECEMBER 2018

ACKNOWLEDGEMENTS

I would like to thank to each and every person who individual who supported and assisted me in completing this thesis. Firstly, I would like to thank to my supervisor, Dr. Mohammed Falah Mohammed for assist, guidance moral support and advice that given to me to finish the development process of the application for this project. My special acknowledgement also goes to my parents, Encik Mohd Dali bin Bakar and Puan Sarimah binti Selaman, my family and my friends who support me mentally and physically throughout the process of completing this project.

ABSTRACT

The MAS model consists of several independents agents, and these agents has the ability to carry out a specific task and to make decisions. When working, these agents will share information with each other. Indirectly, this allows the system to get better predictions. When the constituent agents in a MAS model consist of classifiers, the resulting system is known as a multi-agent classifier system (MACS). In this project, our focus is about mutli-agent classifier system based on heterogeneous classifiers. This is because based on the previous analysis, previous MACS model that used homogeneous type of classifiers i.e., FMMs or EFMM have problem with noise effect and noise tolerance, where both classifiers have no mutant against noise. That could have a negative effect on the classification performance. In fact, learning with noise data can cause false knowledge which will be represented as noisy hyperbox in the topology of the classifier. In order to solve this problem we propose to use a heterogeneous classifiers with pruning strategy that have the ability to reduce noise effects. That could improve the MACS classification performance by overcomes the limitations of each classifier when handling different classification problems.

ABSTRAK

Model MAS terdiri daripada beberapa ejen bebas, dan ejen-ejen ini mempunyai keupayaan untuk menjalankan tugas khusus dan membuat keputusan. Apabila bekerja, ejen-ejen ini akan berkongsi maklumat antara satu sama lain. Secara tidak langsung, ini membolehkan sistem untuk mendapatkan ramalan yang lebih baik. Apabila ejen konstituen dalam model MAS terdiri daripada pengelas, sistem yang dihasilkan dikenali sebagai sistem pengelasan pelbagai agen (MACS). Dalam projek ini, tumpuan kami adalah mengenai sistem pengelas mutli-agen berdasarkan pengkelas yang berbeza. Ini kerana berdasarkan analisis terdahulu, model MACS terdahulu yang menggunakan jenis pengelas yang sama seperti FMM atau EFMM mempunyai masalah dengan kesan bunyi dan toleransi bunyi, di mana kedua-dua pengeluar tidak mempunyai mutan terhadap bunyi. Itu boleh memberi kesan negatif terhadap prestasi klasifikasi. Malah, pembelajaran dengan data bunyi boleh menyebabkan pengetahuan palsu yang akan diwakili sebagai hyperbox yang bising dalam topologi pengelas. Untuk menyelesaikan masalah ini, kami mencadangkan untuk menggunakan pengelas yang sama dengan strategi pemangkasan yang mempunyai keupayaan untuk mengurangkan kesan bunyi. Itu boleh meningkatkan prestasi klasifikasi MACS dengan mengatasi batasan setiap pengelas apabila mengendalikan masalah klasifikasi yang berbeza.

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LIST OF ABBREVIATIONS

MAS	Multi-Agent System
MACS	Multi-Agent Classifier System
MACS-CBS	Multi-Agent Classifier System based on Certified Belief in Strength
TNC-based MACS	Trust-Negotiation-Communication based Multi-Agent Classifier System
ANN	Artificial Neural Network
FMM	Fuzzy Min-Max
EFMM	Enhanced Fuzzy Min-Max
CBS	Certified Belief in Strength
NN	Neural Network

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Many researchers have pay great attention to multi-agent system (MAS) technologies, where various MAS models have been widely used in diverse fields such as power engineering, e-commerce and fault diagnosis. The MAS model consists of several independents agents, and these agents has the ability to carry out a specific task and to make decisions. When working, these agents will share information with each other. Indirectly, this allows the system to get better predictions. When the constituent agents in a MAS model consist of classifiers, the resulting system is known as a multi-agent classifier system (MACS) [1].

MACS consists of two layers. First layer known as manager, meanwhile second layer known as agents (classifier). Agents will undergo learning procedures according to training and prediction. After that, the agent will receive a test sample. Each agent will predict which hyperbox (hence the output class) the test sample that belongs to. Next, the decision made by the agent should be submitted to the manager. Then, the manager will determine the winner. In this model, neural network model used as the learning agents [1].

Artificial neural network (ANN) is a computational model that consists of an interconnected group of artificial neurons that simulates the biological neural system in our brain. Among the problems that occur in terms of ANN training are related to batch learning, which is catastrophic forgetting, where there is some issues in learning systems. In classification, there are two categories type of learning process including online and offline learning [4]. Online learning can be used to overcome stability plasticity dilemma. Fuzzy Min Max (FMM) is some of neural network that supports online learning..

The FMM structure comprises a number of hyperboxes. Since FMM support online learning, every time the data sample arrives, FMM will create a new hyperbox based on that data, and link them to a new class, or improve existing ones without retraining [3]. However, FMM suffers from some limitations belongs to its expansion, overlap test, and contraction processes. Hence, an Enhanced Fuzzy Min-Max (EFMM) network was proposed to overcome the FMM limitations.

In EFMM, the learning process is similar to that in FMM, but there are some improvements in the expansion, overlap test, and contraction processes [3]. EFMM has demonstrated its effectiveness in addressing the first three FMM limitations, but there are still unresolved issues that are related to noise tolerance. Hence, EFMM with pruning has been proposed to solve the limitations of EFMM and enhance its robustness for tackling pattern classification problems [5].

In fact, the technique that have been used to handle noise problem in EFMM with pruning known as pruning strategy. This strategy will reduce the complexity of the network associated with the presence of noise in the training data sample [5]. However, pruning strategy have a drawback related to the size of data and number of patterns, where using a small number of input pattern during the prediction stage could affect the performance quality.

Based on that, we can say that there are advantages and disadvantages for each neural network model. That advantages and disadvantages depends on the type of data sets. Based on that, we propose to use MACS based heterogeneous classifiers instead of using a homogeneous classifiers. That could improve the MACS classification performance by overcomes the limitations of each classifier when handling different classification problems.

1.2 PROBLEM STATEMENT

Based on the previous analysis, previous MACS model used a homogeneous type of classifiers i.e., FMMs or EFMM. The real problem with that design is the noise effect and noise tolerance, where both classifiers have no mutant against nose. That could have a negative effect on the classification performance. In fact, learning with noise data can cause false knowledge which will be represented as noisy hyperbox in the topology of the classifier. Because of that we propose to use a heterogeneous classifiers with pruning strategy that have the ability to reduce noise effects.

1.3 AIM AND OBJECTIVES

The aim of this project is to improve the classification accuracy of the MACS model by using different classifier models. The objectives of this project are:

1. To study and analyse some of the existing pattern classifiers and highlight their limitations and advantages.
2. To propose a heterogeneous MACS with the ability to deal with noise and free noise data sets for pattern classification problems.
3. To test and evaluate the performance of the model by using Iris datasets and Heart datasets.

1.4 SCOPE OF PROJECT

1. The study focus on heterogeneous classifier instead of homogeneous classifier.
2. The proposed model will be test using Iris datasets and Heart datasets.

1.5 SIGNIFICANCE

Proposing a new heterogeneous MACS with the ability to overcome the data noise problems.

1.6 THESIS ORGANIZATION

In chapter 1, we talk about the Multi Agent System in introduction. We also describe more about the neural network, and some of its models, also some explanation about homogeneous and heterogeneous model. Problem statement in this chapter describe the

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